CORE
Metadata, citation and similar papers at core.ac.uk
Provided by Edinburgh Research Explorer

THE UNIVERSITY of EDINBURGH

Edinburgh Research Explorer

Parsimony versus reductionism

Citation for published version:
Seitz, MJ, Templeton, A, Drury, J, Köster, G & Philippides, A 2017, 'Parsimony versus reductionism: How can crowd psychology be introduced into computer simulation?' Review of General Psychology, vol. 21, no. 1, pp. 95-102. DOI: 10.1037/gpr0000092

Digital Object Identifier (DOI):
10.1037/gpr0000092

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Review of General Psychology

Publisher Rights Statement:
The final version of this paper has been published in Review of General Psychology, 21:1, March 2017 by SAGE Publications Ltd, All rights reserved. © Seitz etal, 2017. It is available at: https://journals.sagepub.com/doi/10.1037/gpr0000092

General rights
Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact openaccess@ed.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.

OPEN ACCESS

Download date: 05. Apr. 2019

Parsimony versus reductionism: How can crowd psychology be introduced into computer simulation?

Abstract

Computer simulations are increasingly being used to predict the behaviour of crowds. However, the models used are mainly based on video observations, not an understanding of human decision making. Theories of crowd psychology can elucidate the factors underpinning collective behaviour in human crowds. Yet, in contrast to psychology, computer science must rely upon mathematical formulations in order to implement algorithms and keep models manageable. Here we address the problems and possible solutions encountered when incorporating social psychological theories of collective behaviour in computer modelling. We identify that one primary issue is retaining parsimony in a model whilst avoiding reductionism by excluding necessary aspects of crowd psychology, such as the behaviour of groups. We propose cognitive heuristics as a potential avenue to create a parsimonious model that incorporates core concepts of collective behaviour derived from empirical research in crowd psychology.

Keywords: crowd psychology, pedestrian dynamics, interdisciplinary, social identity approach, collective behaviour

Parsimony versus reductionism: How can crowd psychology be introduced into computer simulation?

Introduction

Computer simulations of pedestrian crowds are being increasingly used for event, transportation and evacuation planning (e.g., Daamen, Duives, & Hoogendoorn, 2014). They can help to ensure comfort and safety, such as for festivals, large sporting events, railway stations, and other indoor environments. The general motivation to develop these simulations is to predict crowd movement. In addition to the practical applications, simulation models may also be used to formalise and test hypotheses from social psychology (Strube, 2000). However, the development of simulation tools that accurately predict human behaviour is still at an early stage. This is partially due to practical limitations; for example, it is difficult to gain in vivo empirical data from emergency situations. Empirical data is necessary for the design and calibration of models given the research question of the study. Additional empirical data is needed for the validation of the calibrated model (e.g., Bandini, Gorrini, & Vizzari, 2014). Even when video footage is available, it maybe be necessary to integrate modern social psychological theories to gain a deeper understanding of crowd behaviour.

There are two major categories of computer simulations for crowd dynamics: microscopic and macroscopic models. With macroscopic models, the overall flow or dynamic of the crowd is simulated, but not the individual pedestrian's behaviour. One particularly important implication from crowd psychology is that there are two types of crowds. On one hand there are physical crowds, which are comprised of numerous individuals or small groups within the crowd. On the other hand, there are psychological crowds where the members of a crowd share a group identity, which affects their behaviour (Reicher & Drury, 2010). Hence, in order to accurately simulate different types of crowds, we need to attend to what type of crowd is being modelled and what assumptions the modellers are making about them. To model behaviour in line with crowd psychology –

where individuals have the ability to become members of groups – microscopic models would be needed.

While the importance of crowd psychology for engineering has been noted (Aguirre, El-Tawil, Best, Gill, & Fedorov, 2011; Sime, 1995), theories of crowd psychology have only been minimally incorporated into mathematical modelling and computer simulations, and from a psychological point of view, these are out-dated (Templeton, Drury, & Philippides, 2015). A more promising direction of research are proxemics (Baum & Paulus, 1987; Hall, 1966), which describe the social distances individuals keep from one another and has been used for the study of crowd behaviour (Costa, 2010; von Sivers & Köster, 2015; Zanlungo, Ikeda, & Kanda, 2014). Although there have been some attempts to introduce small groups within the larger crowd behaviour to simulation models such as families, friends or other predefined groups (Köster, Seitz, Treml, Hartmann, & Klein, 2011; Moussaïd, Perozo, Garnier, Helbing, & Theraulaz, 2010; Singh et al., 2009; Yang, Zhao, Li, & Fang, 2005), these models do not consider the social structure or dynamic of the whole crowd (for a comprehensive review, see (Templeton et al., 2015)). For example, concepts such as "contagion" between individuals are still referred to in recent literature (e.g., Fridman & Kaminka, 2007; Helbing, Farkas, Molnár, & Vicsek, 2002). However, "contagion" was popularized by Le Bon (Le Bon, 1895) in an attempt to explain social influence and homogeneity in crowds and has been challenged by research showing that behaviour in crowds does not spread automatically, but rather is limited by the extent to which participants share a social identity (Reicher, 1984, 1996). Another example is the notion of an irrational "panic" behaviour in disasters at mass events, despite most scientists in the field arguing that "mass panic" is actually a myth (Aguirre, 2005; Drury, Novelli, & Stott, 2013; Johnson, 1987).

Modern social psychology has developed an alternative theory of crowd behaviour based on an extensive programme of empirical evidence: the social identity approach. This approach has been used to understand numerous instances of collective behaviour, including behaviour at riots, protests, religious ceremonies, and music festivals (Abrams & Hogg, 1990; Alnabulsi & Drury, 2014; Drury, Cocking, Reicher, Burton, et al., 2009; Neville & Reicher, 2011; Novelli, Drury, & Reicher, 2010; Reicher, 1984, 1996).

These debates in social psychology are important for the computer simulation of crowds because understanding them may avert relying upon out-dated theories or the use of concepts that are not suitable explanations for particular types of crowds. For example, outdated theories such as "contagion" cannot explain the boundaries of behaviour in crowds that behave together as a cohesive group, such as the coordinated actions one sees in a Mexican wave by supporters of a sports team, or survivors of emergency situations who work together for the sake of the whole crowd.

A correct understanding of current concepts and theories from social psychology is prerequisite to carrying them over to computer simulations. Furthermore, when attempting to simulate phenomena predicted by theories from social psychology, it is also crucial to understand the challenges and limitations that exist in mathematical modelling. In microscopic simulations, the motion of individual virtual humans (hereafter referred to as agents) is simulated. In most microscopic models, the behaviour of agents is highly abstracted from reality and focuses on observable motion in specific scenarios, such as egress from a room through a bottleneck or bi-directional flow (Burstedde, Klauck, Schadschneider, & Zittartz, 2001; Helbing & Molnár, 1995; Seitz & Köster, 2012). The underlying mechanisms producing this behaviour are simple and are usually not primarily aimed at representing the human cognitive process (Moussaïd & Nelson, 2014). This poses a key problem when creating a model with the purpose of realistically simulating the numerous factors of social cognition. We put forward that one avenue to negotiate the complexities of social psychological models with the necessary parsimonious approach of mathematical modelling is through cognitive heuristics (Gigerenzer, 2008; Gigerenzer, Todd, & A.B.C. Research Group, 1999; Seitz, Bode, & Köster, 2016). Cognitive heuristics allow for agents to make flexible decisions based on a set of criteria, which provides ample ground to incorporate cognition we know from social psychology into a rule-based model of social behaviour.

In this article, we aim to examine the difficulties that could arise from merging mathematical modelling and social psychology. In section 2, we provide a short overview on crowd research in social psychology. In section 3, we briefly review main tendencies in pedestrian and crowd computer simulation models. We then discuss the difficulties of introducing concepts from social psychology into simulation models from a theoretical standpoint in section 4. In section 5, we propose cognitive heuristics (Gigerenzer et al., 1999) as a modelling paradigm, which may help to bring crowd psychology and computer simulations closer together. Finally, in section 6, we discuss the arguments presented in this paper and provide an outlook on possible future work in this area.

The study of crowds in social psychology

A brief history of crowd psychology: individuals versus the group

Research on crowd psychology has produced various theories to account for the emergence of collective behaviour in crowds. However, three key approaches have been particularly influential. These are: a) the "group mind" approaches, b) approaches focussing on individuals, and c) contemporary accounts of collective behaviour, which seek to address the relationship between individuals and collective behaviour using the concepts of norm and identity. This section will outline these three approaches.

Within the "group mind" accounts, crowds were understood as homogeneous entities where the individuals in the crowd became indistinguishable from the "mass". Le Bon (1895) suggested that people descend into mindless irrationality upon entering a crowd, where every crowd member shares the same thoughts and is susceptible to manipulation by a leader. Other accounts, such as that of Allport (1924), took the opposite end of the spectrum and argued that there is no sense of "group mind". Instead, the activity of the crowd is merely the behaviour of an aggregate of individuals. Here, rather than people succumbing to a group mind, collective behaviour occurs through social facilitation. Social facilitation means that the presence of others enhances the likelihood of pre-existing behaviours in the individual to emerge. As Allport (1924) says, “the individual in the crowd behaves just as he would behave alone only more so” (p. 295).

Subsequent researchers in crowd psychology argued that neither the theory of a group mind nor theories only considering individuals can adequately explain the social form of collective behaviour – i.e., the fact that crowd behaviour is both coordinated and socially meaningful (Asch, 1952; Reicher, 2001). Following this argument, interactionist approaches, such as that of Sherif (1967), proposed that being in a group has psychological consequences not reducible to those of the individual. The focus of collective behaviour research then turned to investigate how group norms were established, such as the group’s aims, rules and beliefs, and which behaviours were seen to be legitimate or illegitimate by members of the group (R. H. Turner & Killian, 1957).

In the last 30 years, small group approaches in social psychology and approaches emphasizing the individual need to be with familiar others have focused on the relationships between subgroups within a crowd. For example, studies of emergency evacuations indicated that, when in danger, people will attempt to remain with a small group with whom they have pre-existent social ties (Johnson, 1988; Mawson, 2005; Sime, 1983). However, reducing crowd behaviour to the interaction of small groups cannot always explain large-scale collective behaviour since the members of the crowd may cooperate across the borders of pre-existing subgroups. For example, a study of fans at an outdoor music event found that while people arrived mostly in small friendship groups, cooperative behaviours (including assisting others in need, protecting others’ privacy, and coordinating evacuation) were common among strangers (Drury, Novelli, & Stott, 2015).

Towards an understanding of large-scale collective behaviour

One leading approach to explain collective behaviour where the entire crowd acts as a group is self-categorisation theory (J. C. Turner, 1982, 1987). Self-categorisation theory provides the tools to explain why individuals consider themselves members of a group, even when those individuals have not previously interacted. This theory proposes that collective behaviour is based on the process of depersonalisation (J. C. Turner, 1985, 1987). That is, individuals self-stereotype and perceive themselves as being interchangeable with others in that social group. By doing this, individuals shift from their personal identity to their social identity as a member of a particular social group and are therefore able to coordinate their actions with other group members who share the same social identity.

Over the past decade, there has been increased recognition that the concept of a shared social identity is necessary for more realistic simulation of human collective behaviour (Aguirre et al., 2011; Köster et al., 2011; Langston, Masling, & Asmar, 2006; Smith et al., 2009; Templeton et al., 2015). The ability of self-categorisation theory to explain collective behaviour in numerous contexts indicates that computer simulations could benefit from applying this theory to adequately reproduce a broad variety of collective behaviour scenarios. However, it is not obvious how to carry concepts such as self-categorisation over to mathematical modelling and computer simulation. A model based on self-categorisation theory would require agents to be able to have social identities and to coordinate actions with other members of their group. In the next section, we will briefly discuss the main approaches in microscopic computer simulation of human crowds to lay the foundations for understanding this issue.

Computer simulations of crowd behaviour

A variety of crowd models for computer simulation have been proposed. The most basic classification is microscopic versus macroscopic models (e.g., Duives, Daamen, & Hoogendoorn, 2013). In this section, we are only concerned with the microscopic modelling approach in which individual behaviour, but not gross features such as pedestrian flow, is modelled. Although macroscopic models may be useful for some applications, they do not provide the possibility of modelling cognitive processes. Therefore, we argue that macroscopic models are not appropriate for reproducing the phenomena of collective behaviour in crowds.

The first microscopic computer simulation model of crowds known to the authors is that by Gipps and Marksjö (1985), which uses a cellular grid for individual locomotion steps. In this simulation model, each agent occupies one cell in the grid, and occupied cells cannot be entered by other agents. The choice of where to make the next step is made by evaluating the attractiveness of adjacent cells around the current position of an agent. This attractiveness could also be interpreted as utility and the choice of cell as utility optimisation (Seitz, Dietrich, & Köster, 2015). The second approach, by Helbing and Molnár (1995), is based on the idea of "social forces", which are then interpreted as actual physical forces accelerating the agents as in particle physics. Although the authors refer to the original concept of social forces by Lewin (1951), the mathematical formulation and computation is simply that of physical forces. Alternative approaches are probabilistic cellular models (Burstedde et al., 2001), the optimisation of direction and speed according to perceptual cues in the environment (Moussaïd, Helbing, & Theraulaz, 2011; Moussaïd & Nelson, 2014), and stepwise motion and utility optimisation in continuous space (Seitz & Köster, 2012). In the following, we take a step back and investigate simulation models for crowds from a more theoretical standpoint. This standpoint is intended to prepare for the discussion on parsimony and reductionism.

All of the models mentioned, except the one by Moussaïd et al. (2011), are implicitly based on the idea of approach-avoidance motivation (Elliot, 2006). The spatial attractiveness is then interpreted as either potential (causing forces), utility, or probability (Seitz, Dietrich, Köster, & Bungartz, 2016). All of the models are simplifications – or idealisations – of the real world. The models are the results of simultaneous Aristotelian idealisations, because they deliberately omit properties, and Galilean idealisations, as they deliberately distort properties (Frigg & Hartmann, 2012). For example, simulated agents do not have hair colour because this is a superfluous aspect in the simulation, thus following an Aristotelian idealisation. Additionally, an agent's body is represented by a simple geometrical shape, such as circles in a two-dimensional world, which is a Galilean idealisation. Since both types of simplifications are heavily used in crowd modelling, it could be argued that they are caricatures: they only emphasise some aspects of reality. However, the objective is rather that of an approximation, a description of reality in an approximate way (Gibbard & Varian, 1978).

We argue that most microscopic crowd simulation models might be best characterised as phenomenological models (Mcmullin, 1968): they describe observable properties of crowd behaviour, but not their inner workings. For instance, individuals might act in a way that makes it look as though their motion was determined by physical potentials and forces, or utility optimisation, but these concepts do not reflect human cognition (Gigerenzer et al., 1999). Furthermore, observations of crowd movement, as opposed to findings from empirical psychological research, are commonly used for the development or validation of computer models. While observations and controlled experiments of crowd movement are indispensable for the validation of models and the calibration of model parameters (Schadschneider & Seyfried, 2011), the neglect of realistic decision-making processes might inhibit the advancement of simulation models, especially the introduction of group psychology. Simulation models of crowds that not only reproduce the observable outcome but also the cognitive process behind it (Moussaïd & Nelson, 2014) may facilitate the introduction of concepts from social psychology.

From a theoretical standpoint, microscopic crowd models seem to have been developed with one objective: describing some proposed phenomena with a simple mathematical description. In the course of this development process, findings from psychology have been largely neglected. The goal of describing phenomena in a concise way based on local interactions seems to have prevailed so far in computer simulation of crowds, which raises the issue of whether this is justified. If that should be the case, does this description of phenomena represent an intrinsic contradiction to the avoidance of reductionism as discussed in the previous section?

On parsimony and reductionism

There are several arguments for the parsimony of models and theories (Baker, 2013). One argument stands out due to its importance and generality in science: the criterion of falsifiability (Popper, 2002). Falsifiability means that statements (that is, theories) are susceptible to empirical testing such that they can, in principle, be shown by evidence to be false. If there are no deducible hypotheses that can be tested, the theory cannot be considered a scientific theory. If we accept this criterion, it follows that we should not introduce arbitrary or ad hoc extensions to a theory as this would prevent falsification (for an extended analysis, see (Forster & Sober, 1994)).

In the practice of modelling crowds, behaviour for a specific situation or observation could be added to the model in order to match some empirical observation and thereby evade falsification. Furthermore, how many parameters are acceptable in a model before it can no longer be falsified due to its flexibility. Another issue is the overfitting to one particular behaviour rather than creating a model that is applicable to numerous scenarios (Moussaïd & Nelson, 2014).

A crucial point in addressing reductionism is that the simplicity of models may have many facets. A model can be simple in terms of analogies, mathematics, or ease of implementation in software. It may not be immediately obvious which of two models is more concise, due to the multiple criteria for concision. For instance, physicists may find force-based models appealing, whereas computer scientists may prefer optimisation approaches. One criterion with vast practical implications is the computational effort needed to simulate crowd behaviour. This can significantly inhibit scientific investigation of a simulation model: if the computation is not efficient, fewer scenarios can be studied and compared to empirical results. In some practical applications, there are rigid requirements for computational performance. An example is the projection of an ongoing crowd movement scenario into the future as a means of ensuring safety at a mass event.

Other criteria may be reasonable for specific applications, objectives, and research domains. Any of the criteria, whether justified or not or deliberate or not, may influence the choice of modelling approach. However, modellers and practitioners should be aware of the criteria they are using to make an educated decision. Ideally one would select criteria first, possibly weight them, and subsequently choose an approach or model based on these provisions.

In the interest of having a parsimonious model of collective behaviour, it might seem obvious that simple individual “rules of thumb” are preferable to a representation of the group in each agent, as suggested by self-categorisation theory. Nevertheless, this may not always be the case: some phenomena may be more concisely described with the latter category of models with a representation of the group in each agent. For example, the behaviour of two conflicting groups, such as the fans of opposing sport teams, can be understood using the social identity approach but is difficult to explain using individualistic theories. It is more plausible, and simpler, to suggest that their common chants, emotions and reactions to each other are a function of their common identities and common relationship to each other, rather than suggesting there is a coincidence of reaction among multiple individual personalities. This explains why a model for individual commuters walking on a pavement in contraflow cannot be used to model how fans of opposing teams interact when walking next to each other: the dynamics in a physical crowd of commuters is fundamentally different from the dynamics of a psychological crowd of fans.

Another demand for parsimony arises from mathematical modelling itself. That is, the requirements for a simulation model are strict: one can only implement an algorithm that simulates behaviour if all phenomena and processes have been formally determined;

vagueness and loose ends are not acceptable.

Certainly the need for parsimony in social psychological models is as important as the need for parsimony in mathematical modelling. However, models and theories in social psychology are often complex and nuanced due to the complexity of real world social phenomena. Even in highly controlled laboratory experiment it is difficult to control all the factors which could influence the outcome. Social psychological models and theories tend to – by necessity due to the openness of social worlds – have unknown parameters, which makes them difficult to implement into an algorithmic description. In mathematical modelling, on the other hand, mathematical systems are concise and closed. The open character and large number of parameters presents a challenge to implementing social psychology into mathematical modelling and eventually to developing an algorithmic description.

In contrast to the idea of parsimony described above, we consider reductionism as an inappropriate or insufficient account of real facts. In crowd psychology, reductionism occurs when either psychological groups or individuals are not included in accounts of collective behaviour. This is also seen in simulation models: most microscopic models only consider local interactions among individuals without a representation of group structures (Duives et al., 2013; Templeton et al., 2015; Zheng, Zhong, & Liu, 2009). In microscopic simulations, the crowd's behaviour is expected to emerge from simple interactions between individuals. This could be one reason why microscopic simulation models tend to be based on local interactions without the consideration of more complex social structures within the crowd. Although subgroup behaviour may be one (important) step in the direction of a more socially structured crowd, scenarios where the crowd acts together as a group, such as in emergency situations, are still neglected (Drury, Cocking, & Reicher, 2009a; Drury, Cocking, Reicher, Burton, et al., 2009).

If we consider it evident that there are group processes which cannot be described by simple local interactions among agents, then neglecting these group processes would be reductionist. Ignoring group processes may not be a problem in scenarios where social identities do not influence the crowd's behaviour, such as in a physical crowd of commuters, who may not share a social identity in general (Drury, Cocking, & Reicher, 2009b). However, if we want to explain more complex collective behaviour, then we may have to consider developing simulation models with an explicit representation of psychological groups in each agent.

There are some key aspects of self-categorisation theory that could be used for simulation models. As mentioned previously, agents must be capable of recognising their own group identity and the group identity of other agents, and capable of acting as an individual or as a group member depending on their salient identity at the time. Given these prerequisites, behaviours resulting from a social identity process could be introduced into decision-making of agents, which would allow for a more profound form of cooperation and collective behaviour.

A primarily phenomenological approach to crowd simulation poses a problem: the models themselves were not necessarily designed to be extendible, flexible, or to include higher levels of complexity in collective behaviour. While this problem might have prohibited the introduction of models from social psychology, it is possible to introduce additional behaviour to existing models. For instance, subgroups have been introduced successfully to force-based models (Moussaïd et al., 2010).

The situation is challenging due to the complexity of social interactions and human behaviour and the requirement of precise mathematical formulation of models for computer simulations. Furthermore, the objectives are somewhat opposing: on the one hand, we hope to avoid reductionism by providing an explanation for complex behaviour, and on the other hand, we try to ensure parsimony by keeping theories and models concise. This is not a contradiction specific to the development of crowd simulation models but rather a general challenge in all of science.

Parsimony without reductionism

Two approaches for simulation of social aspects in crowds

In this section, we discuss two approaches that may allow for the simulation of a social identity process with agents. First, one can try to extend existing models with a social layer in addition to the basic interaction and locomotion mechanisms (Köster et al., 2011; Moussaïd et al., 2010; Singh et al., 2009; von Sivers, Templeton, Köster, Drury, & Philippides, 2014; Yang et al., 2005). Second, one could develop a new decision-making framework that provides the necessary structure and flexibility we need. The first approach seems appealing as existing models have been calibrated and tested with empirical data for certain phenomena. One could strive to build on these achievements. We would need to use and alter the existing mechanisms in such models, which could render previous testing and calibration invalid. Finally, the available mechanism might not provide the necessary modelling flexibility. In the following paragraphs, we present arguments for the second approach although we consider both approaches valuable.

In the literature, agent-based modelling (e.g., Bonabeau, 2002; Goldstone & Janssen, 2005) has been proposed as an approach that might provide the necessary modelling flexibility. The term "agent-based modelling" has been used with different meanings. We define it as an approach with simulated pedestrians (agents) that have individual attributes, goals and cognition. Some authors use an existing interaction and locomotion model, such as the social force model, and extend it to meet their requirements (Zheng et al., 2009). In other words, those models fall into the first category described in the previous paragraph.

The main critique here is that although agent-based models are often very flexible, most do not make use of contemporary concepts from psychology and do not compare their results with empirical data. Thus, while agent-based models can be interesting from an engineering standpoint, they may not be suitable for credible scientific theories. This does not mean agent-based models are inappropriate for this purpose in general, but it has to be shown that it is possible to deduce testable hypotheses from them.

Instead of extending existing local interaction and locomotion models, or using agent-based models, an alternative is to approximate human decision-making processes (Moussaïd et al., 2011; Moussaïd & Nelson, 2014; Zanlungo, Ikeda, & Kanda, 2012). In the following section, we propose this approach as a modelling paradigm that may have advantages.

Towards cognitive modelling

How could the attempt to model agents' behaviour according to more plausible cognitive decision-making processes help in the predicament of avoiding reductionism and maintaining parsimony at the same time? First, cognitive modelling would lead away from a merely behavioural (that is, phenomenological) explanation to theories attempting to explain the underlying processes (Moussaïd & Nelson, 2014). This itself could be seen as advantageous. Second, cognitive modelling might provide the necessary flexibility and expandability in crowd models to allow the introduction of aspects of psychology not previously incorporated. For example, in this paper we argue for the incorporation of the social identity approach, which may motivate using cognitive modelling. Third, one could expect that more plausible decision-making processes also lead to more plausible behaviour of simulated agents.

As a fundamental paradigm for cognitive modelling, we suggest to use bounded rationality (Newell & Simon, 1972) and cognitive heuristics (Gigerenzer, 2008; Gigerenzer et al., 1999; Muntanyola-Saura, 2014). The proponents of this paradigm argue that human decision making has to be based on evolutionary developed cognitive capacities, such as the ability to estimate distances or predict movement based on previous movement cues. Furthermore, they suggest that humans do not make decisions based on mathematical optimisation, but rather employ simple heuristics, which may or may not lead to the optimal solution and do not require unbounded computational power.

Gigerenzer calls the collection of heuristics used by an individual an adaptive toolbox (Gigerenzer et al., 1999). This suggests that various heuristics can be used for decision making tasks, which introduces high modelling flexibility. Does this mean the adaptive toolbox is a theory that easily introduces ad hoc hypotheses without ever becoming falsifiable? Indeed, the hypothesis that humans make decisions based on cognitive heuristics cannot be easily falsified: it is a higher order assumption or perspective that must be tested on another level. The concrete heuristics, however, are hypotheses themselves, and their predictions can be tested.

Cognitive heuristics represent plausible decision-making processes and have already been used to describe local avoidance behaviour of pedestrians (Seitz, Bode, & Köster, 2016). They also seem appropriate for specific behavioural aspects, for example, the route choice in complex spatial layouts (e.g., Hoogendoorn & Bovy, 2004; Kneidl, Borrmann, & Hartmann, 2012). Therefore, we can also consider this approach to be suitable for the introduction of models from crowd psychology, such as self-categorization theory, which is already a social and cognitive model (J. C. Turner, 1987). While some core aspects of the social identity approach may not be cognitive, such as the importance of social context (or social reality), these aspects could still function together with a cognitive model. For instance, the extent to which a person categorises one's self within the group at a specific moment is influenced by the social environment (J. C. Turner, Oakes, Haslam, & McGarty, 1994). A cognitive model for agents and a formal model for the social identity approach may be parsimonious and simultaneously avoid reductionism if they can explain some collective behaviour that has not yet been captured in computer modelling, such as fans of opposing sport teams.

Discussion

Throughout this article we have discussed crowd psychology, crowd computer simulation and the challenges that arise from their interdisciplinary nature. Our focus has been to examine the seemingly contradictory tendencies between parsimony in simulation modelling while avoiding reductionism in social psychology. We have brought forward the argument that both are legitimate objectives in science, but could be somewhat in opposition to each other. However, this opposition does not seem to be a problem specific to the development of crowd simulations. We have argued that these two principles constitute general opponents in science: should we make models more complex to explain more features of reality and avoid reductionism, which, in turn, may make them less parsimonious?

Due to the extensive empirical research on crowd behaviour, social psychology is clearly important for crowd simulation modelling. In the end, what we want to reproduce or predict is human behaviour in varying social environments and settings. Most research in crowd simulation has focused on purely observable features, such as flow and densities, which are very important and can be used for practical applications (Schadschneider et al., 2009). However, this focus might inhibit the development of simulation models in the future and prohibit the carry-over of established concepts from psychology.

Simulation models could be beneficial for studying crowd models in social psychology and vice versa. The use of crowd simulation models can help to formalize and investigate theories from social psychology in a closed environment, which might lead to a better understanding of crowd models. We understand the interdisciplinary discussions as presented in this paper not only challenging but also as a fruitful and constructive way to develop theories in both simulation modelling and social psychology.

We expect cognitive models for pedestrian behaviour to be constructive in future research. In general, this would require a stronger engagement by mathematical modellers in cognitive sciences and psychology from mathematical modellers. Moussaïd et al. (2011) have described a model that points in that direction attempting to explain pedestrian behaviour with simple rules. Following this approach, we put forward the concept of cognitive heuristics (Gigerenzer, 2008; Gigerenzer et al., 1999; Muntanyola-Saura, 2014), which is not a model itself, but a paradigm describing how to model human decision-making.

Social psychology and computer modelling are both being used separately to plan and monitor safety at mass crowd events. By combining their knowledge, together these disciplines could have a real and important impact on the safety of large crowd events. Many challenges remain in computer simulation of human crowds. Empirical validation of candidate models may be infeasible if the scenarios, such as disasters, are not observed often. We argue, however, that the integration of findings from social sciences is a promising avenue for future simulation model development.

References

Abrams, D., & Hogg, M. A. (1990). Social identity theory: Constructive and critical advances. In D. Abrams & M. A. Hogg (Eds.), (pp. 1–9). New York: Springer.

Aguirre, B. E. (2005). Commentary on "understanding mass panic and other collective responses to threat and disaster": Emergency evacuations, panic, and social psychology. *Psychiatry*, *68*(2), 121–129.

Aguirre, B. E., El-Tawil, S., Best, E., Gill, K. B., & Fedorov, V. (2011). Contributions of social science to agent-based models of building evacuation. *Contemporary Social Science*, *6*(3), 415–432.

Allport, F. H. (1924). *Social psychology.* Boston: Houghton Mifflin Company.

Alnabulsi, H., & Drury, J. (2014). Social identification moderates the effect of crowd density on safety at the Hajj. *Proceedings of the National Academy of Sciences*, *111*(25), 9091–9096.

Asch, S. E. (1952). *Social psychology.* New Jersey: Prentice Hall.

Baker, A. (2013). Simplicity. In E. N. Zalta (Ed.), *The stanford encyclopedia of philosophy* (Fall 2013 ed.). Metaphysics Research Lab, Center for the Study of Language and Information, Stanford University. online.

Bandini, S., Gorrini, A., & Vizzari, G. (2014). Towards an integrated approach to crowd analysis and crowd synthesis: A case study and first results. *Pattern Recognition Letters*, *44*, 16–29.

Baum, A., & Paulus, P. B. (1987). Handbook of environmental psychology. In D. Stokols & I. Altman (Eds.), (pp. 533–570). New York: Wiley.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7280–7287.

Burstedde, C., Klauck, K., Schadschneider, A., & Zittartz, J. (2001). Simulation of pedestrian dynamics using a two-dimensional cellular automaton. *Physica A:*

Statistical Mechanics and its Applications, *295*, 507–525.

Costa, M. (2010). Interpersonal distances in group walking. *Journal of Nonverbal Behavior*, *34*(1), 15–26.

Daamen, W., Duives, D. C., & Hoogendoorn, S. P. (Eds.). (2014). *The conference in pedestrian and evacuation dynamics 2014 (ped 2014)* (Vol. 2). Delft, The Netherlands: Elsevier.

Drury, J., Cocking, C., & Reicher, S. (2009a). Everyone for themselves? A comparative study of crowd solidarity among emergency survivors. *British Journal of Social Psychology*, *28*, 487–506.

Drury, J., Cocking, C., & Reicher, S. (2009b). The nature of collective resilience: Survivor reactions to the 2005 London bombings. *International Journal of Mass Emergencies and Disasters*, *27*(1), 66–95.

Drury, J., Cocking, C., Reicher, S., Burton, A., Schofield, D., Hardwick, A., ... Langston, P. (2009). Cooperation versus competition in a mass emergency evacuation: A new laboratory simulation and a new theoretical model. *Behavior Research Methods*, *41*(3), 957–970.

Drury, J., Novelli, D., & Stott, C. (2013). Representing crowd behaviour in emergency planning guidance: 'mass panic' or collective resilience? *Resilience: International Policies, Practices and Discourses*, *1*, 18–37.

Drury, J., Novelli, D., & Stott, C. (2015). Managing to avert disaster: Explaining collective resilience at an outdoor music event. *European Journal of Social Psychology*, *45*(4), 533–547.

Duives, D. C., Daamen, W., & Hoogendoorn, S. P. (2013). State-of-the-art crowd motion simulation models. *Transportation Research Part C: Emerging Technologies*, *37*(0), 193–209.

Elliot, A. J. (2006). The hierarchical model of approach-avoidance motivation. *Motivation and Emotion*, *30*(2), 111–116.

Forster, M., & Sober, E. (1994). How to tell when simpler, more unified, or less ad hoc theories will provide more accurate predictions. *The British Journal for the Philosophy of Science*, *45*(1), 1–35.

Fridman, N., & Kaminka, G. A. (2007). Towards a cognitive model of crowd behavior based on social comparison theory. In *AAAI Conference on Artificial Intelligence.*

Frigg, R., & Hartmann, S. (2012). Models in science. In E. N. Zalta (Ed.), *The stanford encyclopedia of philosophy* (Fall 2012 ed.). Metaphysics Research Lab, Center for the Study of Language and Information, Stanford University. online.

Gibbard, A., & Varian, H. R. (1978). Economic models. *The Journal of Philosophy*, *75*(11), 664–677.

Gigerenzer, G. (2008). Why heuristics work. *Perspectives on Psychological Science*, *3*(1), 20–29.

Gigerenzer, G., Todd, P. M., & A.B.C. Research Group. (1999). *Simple heuristics that make us smart.* Oxford: Oxford University Press.

Gipps, P., & Marksjö, B. (1985). A micro-simulation model for pedestrian flows. *Mathematics and Computers in Simulation*, *27*(2–3), 95–105.

Goldstone, R. L., & Janssen, M. A. (2005). Computational models of collective behavior. *Trends in Cognitive Sciences*, *9*(9), 424–430.

Hall, E. T. (1966). *The hidden dimension.* New York: Doubleday.

Helbing, D., Farkas, I. J., Molnár, P., & Vicsek, T. (2002). Simulation of pedestrian crowds in normal and evacuation situations. In *Pedestrian and evacuation dynamics 2002.*

Helbing, D., & Molnár, P. (1995). Social Force Model for pedestrian dynamics. *Physical Review E*, *51*(5), 4282–4286.

Hoogendoorn, S. P., & Bovy, P. H. L. (2004). Pedestrian route-choice and activity scheduling theory and models. *Transportation Research Part B: Methodological*, *38*(2), 169–190.

Johnson, N. R. (1987). Panic and the breakdown of social order: Popular myth, social theory, empirical evidence. *Sociological Focus*, *20*(3), 171–183.

Johnson, N. R. (1988). Fire in a crowded theater: A descriptive investigation of the emergence of panic. *International Journal of Mass Emergencies and Disasters*, *6*(1), 7–26.

Kneidl, A., Borrmann, A., & Hartmann, D. (2012). Generation and use of sparse navigation graphs for microscopic pedestrian simulation models. *Advanced Engineering Informatics*, *26*(4), 669–680.

Köster, G., Seitz, M., Treml, F., Hartmann, D., & Klein, W. (2011). On modelling the influence of group formations in a crowd. *Contemporary Social Science*, *6*(3), 397–414.

Langston, P. A., Masling, R., & Asmar, B. N. (2006). Crowd dynamics discrete element multi-circle model. *Safety Science*, *44*(5), 395–417.

Le Bon, G. (1895). *La psychologie des foules*. Alcan.

Lewin, K. (1951). *Field theory in social science: Selected theoretical papers* (D. Cartwright, Ed.). New York: Harper.

Mawson, A. R. (2005). Understanding mass panic and other collective responses to threat and disaster. *Psychiatry*, *68*(2), 95–113.

Mcmullin, E. (1968). What do physical models tell us? In B. V. Rootselaar & J. F. Staal (Eds.), *Logic, Methodology and Philosophy of Science III* (Vol. 52, pp. 385–396). Elsevier.

Moussaïd, M., Helbing, D., & Theraulaz, G. (2011). How simple rules determine pedestrian behavior and crowd disasters. *Proceedings of the National Academy of Sciences*, *108*(17), 6884–6888.

Moussaïd, M., & Nelson, J. D. (2014). Simple heuristics and the modelling of crowd behaviours. In U. Weidmann, U. Kirsch, & M. Schreckenberg (Eds.), *Pedestrian and evacuation dynamics 2012* (pp. 75–90). Springer International Publishing.

Moussaïd, M., Perozo, N., Garnier, S., Helbing, D., & Theraulaz, G. (2010). The walking behaviour of pedestrian social groups and its impact on crowd dynamics. *PLoS ONE*, *5*(4), e10047.

Muntanyola-Saura, D. (2014). A cognitive account of expertise: Why rational choice theory is (often) a fiction. *Theory & Psychology*, *24*(1), 19–39.

Neville, F., & Reicher, S. (2011). The experience of collective participation: shared identity, relatedness and emotionality. *Contemporary Social Science*, *6*(3), 377–396.

Newell, A., & Simon, H. A. (1972). *Human problem solving*. Longman Higher Education.

Novelli, D., Drury, J., & Reicher, S. (2010). Come together: Two studies concerning the impact of group relations on personal space. *British Journal of Social Psychology*, *49*(2), 223–236.

Popper, K. (2002). *The logic of scientific discovery (1934, 1959).* London and New York: Routledge Classics.

Reicher, S. D. (1984). The St. Pauls' riot: An explanation of the limits of crowd action in terms of a social identity model. *European Journal of Social Psychology*, *14*(1), 1–21.

Reicher, S. D. (1996). 'The Battle of Westminster': developing the social identity model of crowd behaviour in order to explain the initiation and development of collective conflict. *European Journal of Social Psychology*, *26*(1), 115–134.

Reicher, S. D. (2001). Blackwell handbook of social psychology: Group processes. In M. A. Hogg & R. S. Tindale (Eds.), (pp. 182–208). Wiley-Blackwell.

Reicher, S. D., & Drury, J. (2010). Identity and participation in culturally diverse societies. In A. E. Azzi, X. C. Associate, B. Klandermans, & B. Simon (Eds.), (pp. 158–175). Oxford, UK: Wiley-Blackwell.

Schadschneider, A., Klingsch, W., Klüpfel, H., Kretz, T., Rogsch, C., & Seyfried, A. (2009). Evacuation dynamics: Empirical results, modeling and applications. In R. A. Meyers (Ed.), *Encyclopedia of complexity and systems science* (pp. 3142–3176). New York: Springer.

Schadschneider, A., & Seyfried, A. (2011). Empirical results for pedestrian dynamics and their implications for modeling. *Networks and Heterogeneous Media*, *6*(3), 545–560.

Seitz, M. J., Bode, N. W. F., & Köster, G. (2016). How cognitive heuristics can explain social interactions in spatial movement. *Journal of the Royal Society Interface*, *13*(121), 20160439.

Seitz, M. J., Dietrich, F., & Köster, G. (2015). The effect of stepping on pedestrian trajectories. *Physica A: Statistical Mechanics and its Applications*, *421*, 594–604.

Seitz, M. J., Dietrich, F., Köster, G., & Bungartz, H.-J. (2016). The superposition principle: A conceptual perspective on pedestrian stream simulations. *Collective Dynamics*, *1*, A2.

Seitz, M. J., & Köster, G. (2012). Natural discretization of pedestrian movement in continuous space. *Physical Review E*, *86*(4), 046108.

Sherif, M. (1967). *Group conflict and co-operation: Their social psychology.* London: Routledge & Kegan Paul.

Sime, J. D. (1983). Affiliative behaviour during escape to building exits. *Journal of Environmental Psychology*, *3*(1), 21–41.

Sime, J. D. (1995). Crowd psychology and engineering. *Safety Science*, *21*(1), 1–14.

Singh, H., Arter, R., Dodd, L., Langston, P., Lester, E., & Drury, J. (2009). Modelling subgroup behaviour in crowd dynamics DEM simulation. *Applied Mathematical Modelling*, *33*(12), 4408–4423.

Smith, A., James, C., Jones, R., Langston, P., Lester, E., & Drury, J. (2009). Modelling contra-flow in crowd dynamics DEM simulation. *Safety Science*, *47*(3), 395–404.

Strube, G. (2000). Generative theories in cognitive psychology. *Theory & Psychology*, *10*(1), 117–125.

Templeton, A., Drury, J., & Philippides, A. (2015). From mindless masses to small groups: Conceptualizing collective behavior in crowd modeling. *Review of General Psychology*, *19*(3), 215–229.

Turner, J. C. (1982). Towards a cognitive redefinition of the social group. In H. Tajfel

(Ed.), *Social identity and intergroup relations* (pp. 15–40). Cambridge: Cambridge University Press.

Turner, J. C. (1985). Social categorization and the self-concept: A social cognitive theory of group behavior. *Advances in group processes*, *2*, 77–122.

Turner, J. C. (1987). Rediscovering the social group: A self-categorization theory. In J. C. Turner (Ed.), (pp. 68–88). Oxford: Basil Blackwell.

Turner, J. C., Oakes, P. J., Haslam, S. A., & McGarty, C. (1994). Self and collective: Cognition and social context. *Personality and Social Psychology Bulletin*, *20*, 454–463.

Turner, R. H., & Killian, L. (1957). *Collective behaviour.* Englewood Cliffs, NJ: Prentice Hall.

von Sivers, I., & Köster, G. (2015). Dynamic stride length adaptation according to utility and personal space. *Transportation Research Part B: Methodological*, *74*, 104 – 117.

von Sivers, I., Templeton, A., Köster, G., Drury, J., & Philippides, A. (2014). Humans do not always act selfishly: Social identity and helping in emergency evacuation simulation. In *The conference in pedestrian and evacuation dynamics 2014* (pp. 585–593). Delft, The Netherlands.

Yang, L., Zhao, D., Li, J., & Fang, T. (2005). Simulation of the kin behavior in building occupant evacuation based on cellular automaton. *Building and Environment*, *40*(3), 411–415.

Zanlungo, F., Ikeda, T., & Kanda, T. (2012). A microscopic "social norm" model to obtain realistic macroscopic velocity and density pedestrian distributions. *PLoS ONE*, *7*(12), e50720.

Zanlungo, F., Ikeda, T., & Kanda, T. (2014). Potential for the dynamics of pedestrians in a socially interacting group. *Physical Review E*, *89*, 012811.

Zheng, X., Zhong, T., & Liu, M. (2009). Modeling crowd evacuation of a building based on seven methodological approaches. *Building and Environment*, *44*(3), 437–445.